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COLOR IMAGE DISCRIMINATION MODEL FOR GENDER FACE RECOGNITION

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ABSTRACT

Face recognition is one of the biometric methods which are commonly used for the identification of human beings. To identify given face image using main features of the face biometric methods are used. The objective of face recognition involves the extraction of different features of the human face from the face image for discriminating it from other persons. To seek a meaningful representation and an effective recognition method of color images in a unified framework, color image representation and recognition is integrated into one discriminant analysis model: color image discriminant (CID) model. The two sets of variables can be determined optimally and simultaneously by the CID algorithms. A CID model for two-class recognition problems contains one color component combination coefficient vector and one discriminant projection basis vector. A CID algorithm with two class recognition problem is designed for gender classification.

KEYWORDS: Color Image Discriminant (CID), Color Space, Color Images, Gender Classification

INTRODUCTION

Color is the brains reaction to a specific visual stimulus. Although we can precisely describe color by measuring it’s intensity of the visible electro-magnetic radiation at many discrete wavelengths which this leads to a large degree of redundancy. The reason for this redundancy is that the eye’s retina samples color using only three broad bands, roughly corresponding to red, green and blue light. The signals from these color sensitive cells (cones), together with those from the rods (sensitive to intensity only), are combined in the brain to give several different “sensations” of the color. A color space is a method by which we can specify, create and visualize color. A color is thus usually specified using three co-ordinates, or parameters. These parameters describe the position of the color within the color space being used.

Color provides a useful feature for object detection, tracking and recognition, image (or video) segmentation, etc. Color constancy algorithms and color histogram techniques provide efficient tools for object recognition under varying lighting conditions. Different color spaces (or color models) possess different characteristics and are suitable for different visual tasks. For instance, the HSV color space and the YC_bC_r color space are effective for face detection, while the modified L*u*v* color space is useful for image segmentation. Recently, a selection and fusion scheme of multiple color models was investigated and applied for feature detection in images. Although color has been demonstrated helpful for face detection and tracking, some past research suggests that color appears to confer no significant face recognition advantage beyond the luminance information. Recent research efforts, however, reveal that color may provide useful information for face recognition. The experimental results in [2] show that the principal component analysis (PCA) method using color information can improve the recognition rate compared to the same method using only luminance information. The results in [3] further demonstrate that color cues can significantly improve recognition performance compared with intensity-based features for coping with low-resolution face images.

Facial recognition technology (FRT) has emerged as an attractive solution to address many contemporary needs for identification and the verification of identity claims. It brings together the promise of other biometric systems, which

attempt to tie identity to individually distinctive features of the body, and the more familiar functionality of visual surveillance systems. Most face recognition (FR) methods have been developed under the assumption that face image sets consist of gray scale still images. Indeed, the use of gray scale images is a common practice for conventional FR applications. Recently, however, considerable research efforts have been dedicated to the development of face recognition methods that utilize face color information. Results reported in these works indicate that face color information can play an important role in face recognition and it can be used to considerably enhance face recognition performance.

Face recognition has been attracting substantial attention from the researchers in the computer vision, pattern recognition, and machine learning communities. Many face recognition methods have been developed over the years, however, due to the complexity of the problem more robust techniques are yet to be developed to address the grand challenge issues, such as the image variability's in terms of illumination, pose, facial expression, aging, etc. To seek a meaningful representation and an effective recognition method of color images in a unified framework integrating color image representation and recognition into one discriminant analysis model: color image discriminant (CID) model.

In contrast to the classical FLD method, which involves only one set of variables (one or multiple discriminant projection basis vectors) [4], the CID models involve two sets of variables: a set of color component combination coefficients for color image representation and one or multiple discriminant projection basis vectors for image discrimination. The two sets of variables can be determined optimally and simultaneously by the CID algorithms [1].

MOTIVATION

Different color spaces (or color models) possess different characteristics and have been applied for different visual tasks. One common practice is to convert color images in the RGB color space into an intensity image by averaging the three color component images before applying a face recognition algorithm for recognition. Other research effort is to choose an existing color space or a color component configuration for achieving good recognition performance with respect to a specific recognition method. One common practice is to linearly combine its three color components into one intensity image.

$$I = \frac{1}{3}R + \frac{1}{3}G + \frac{1}{3}B \tag{1}$$

The intensity image I is then used to represent A for recognition. However, theoretical explanation is lacking in supporting that such an intensity image is a good representation of image A for image recognition. Here the goal of color image discriminant model, is to find a set of optimal coefficients to combine the R, G, and B color components within a discriminant analysis framework so that is the best representation of the color image for image recognition. Specifically, let D be the combined image given below:

$$D = x_1R + x_2G + x_3B \tag{2}$$

Where, x_1, x_2 and x_3 are the color component combination coefficients.

COLOR IMAGE DISCRIMINATION MODEL

A CID model is first derived for two-class recognition problems. The CID model contains one color component combination coefficient vector and one discriminant projection basis vector. The use of Lagrange multiplier method to solve the optimization problem that the CID model involves and design a CID algorithm to seek the optimal solution by solving two associated, generalized eigen equations iteratively.

Let c be the number of pattern classes, A_{ij} be the jth color image in class i, where i = 1,2,……,c, j = 1,2,………M_i, and M_i denote the number of training samples in class i. The mean image of the training samples in class i is

$$\overline{A_i} = \frac{1}{M_i}\sum_{j=1}^{M_i} A_{ij} = [\overline{R_i}, \overline{G_i}, \overline{B_i}] \tag{3}$$

The mean image of all training samples is

$$\overline{A} = \frac{1}{M}\sum_{i=1}^{c}\sum_{j=1}^{M_i} A_{ij} = [\overline{R}, \overline{G}, \overline{B}] \tag{4}$$

Where M is the total number of training samples. The combined image of three color components of the color image $A_{ij} = [R_{ij}, G_{ij}, B_{ij}]$ is given by

$$D_{ij} = x_1 R_{ij} + x_2 G_{ij} + x_3 B_{ij}$$

$$= [R_{ij}, G_{ij}, B_{ij}]X \tag{5}$$

Where $X = [x_1, x_2, x_3]^T$ is a color component combination coefficient vector. The between-class scatter matrix $S_b(X)$ and the within-class scatter matrix $S_w(X)$ in the D-space are defined as follows:

$$S_b(X) = \sum_{i=1}^{c} P_i [(\overline{A_\imath} - \overline{A})^T X X^T (\overline{A_\imath} - \overline{A})] \tag{6}$$

$$S_w(X) = \sum_{i=1}^{c} P_i \frac{1}{M_i - 1} \times \sum_{j=1}^{M_i}[(\overline{A_\imath} - \overline{A})^T X X^T (\overline{A_\imath} - \overline{A})] \tag{7}$$

Where P_i is the prior probability for class I and commonly evaluated as $P_i = M_i /M$. Because the combination coefficient vector X is an unknown variable, the elements in $S_b(X)$ and $S_w(X)$ can be viewed as linear functional of X. The foregoing criterion is equivalent to the following criterion:

$$J(\varphi, X) = \frac{\varphi^T S_B(X)\varphi}{\varphi^T S_W(X)\varphi} \tag{8}$$

Where φ is a discriminant projection basis vector, $\varphi \neq 0$, and $X \neq 0$. The criterion function is a generalized Rayleigh quotient if X is fixed.

From the property of the generalized Rayleigh quotient, the maximum point of the function exists on the elliptic spherical surface $\{\varphi | \varphi^T S_W(X)\varphi = 1, \varphi \in R^N\}$. Therefore, maximizing the criterion in (8) is equivalent to solving the following optimization model with max $\varphi^T S_b(X)\varphi$ for max φ, X subject to $\varphi^T S_W(X)\varphi = 1$. We will design an iterative algorithm to simultaneously determine the optimal discriminant projection basis vector φ^* and the optimal combination coefficient vector X^*.

COLOR IMAGE DISCRIMINATION ALGORITHM

For the CID Algorithm first, define the color-space between-class scatter matrix $L_b(\varphi)$ and the color-space within-class scatter matrix $L_w(\varphi)$ as follows:

$$L_b(\varphi) = \sum_{i=1}^{c} P_i [(\overline{A_\imath} - \overline{A})^T \varphi \varphi^T (\overline{A_\imath} - \overline{A})] \tag{9}$$

$$L_w(\varphi) = \sum_{i=1}^{c} P_i \frac{1}{M_i - 1} \times \sum_{j=1}^{M_i}[(\overline{A_\imath} - \overline{A})^T \varphi \varphi^T (\overline{A_\imath} - \overline{A})] \tag{10}$$

$L_b(\varphi)$ and $L_w(\varphi)$ are, therefore, 3×3 nonnegative-definite matrices. Actually, $L_b(\varphi)$ and $L_w(\varphi)$ can be viewed as dual matrices of $S_b(X)$ and $S_w(X)$.

If X is fixed, the maximum point φ^* of $J_F(\varphi, X)$ can be chosen as the eigenvector of the generalized equation $S_b(X)\varphi = \lambda S_W(X)\varphi$ corresponding to the largest eigenvalue, and if φ is fixed, the maximum point X^* of $J_F(\varphi, X)$ can be chosen as the eigenvector of the generalized equation $L_b(X)\varphi = \lambda L_W(X)\varphi$ corresponding to the largest eigenvalue. Based on this conclusion, we can design an iterative algorithm to calculate the maximum points φ^* and X^*.

Let $X = X^{[k]}$ be the initial value of the combination coefficient vector in the kth iteration. In the first step, we construct $S_b(X)$ and $S_w(X)$ and calculate their generalized eigenvector $\varphi = \varphi^{[k+1]}$ corresponding to the largest eigenvalue. In the second step, we construct $L_b(\varphi)$ and $L_w(\varphi)$ and calculate their generalized eigenvector $X^{[k+1]}$ corresponding to the largest eigenvalue. $X = X^{[k+1]}$ is used as initial value in the next iteration.

The CID algorithm performs the preceding two steps successively until it converges. Convergence may be determined by observing when the value of the criterion function stops changing. Specifically, after k+1 times of iterations, if $|J(\varphi^{[k+1]}, X^{[k+1]}) - J(\varphi^{[k]}, X^{[k]})| < \varepsilon$, we think the algorithm converges. Then, we choose $\varphi^* = \varphi^{[k+1]}$ and $X^* = X^{[k+1]}$. The CID algorithm is illustrated in Figure 1.

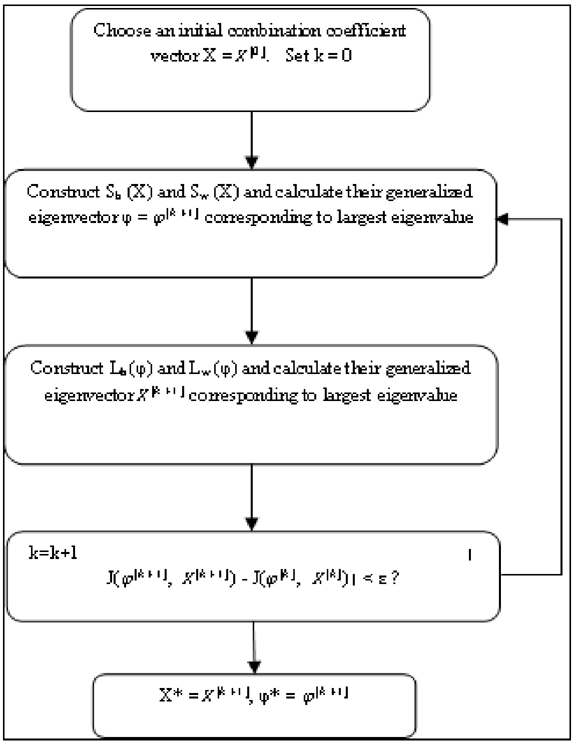

Figure 1: Overview of the Basic CID Algorithm [1]

RESULTS

To assess the performance of the model and algorithm a large scale color image database is required. The controlled images have good image quality, while the uncontrolled images display poor image quality, such as large illumination variations, low resolution of the face region, and possible blurring. In the experiments, the face region of each image is first cropped from the original high-resolution still images and resized to a spatial resolution of 32 × 32.

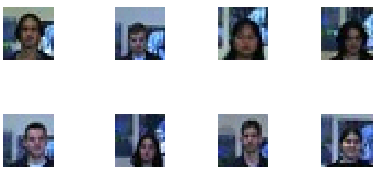

Figure 2: Color Images Cropped in 32 × 32

Now, manually label male or female for each image in the database and then train the basic CID algorithm using the standard training set, which contains some male images and female images. The initial value of the basic CID algorithms is chosen as $X^{[0]} = [1/5,1/5,1/5]$, which is the combination coefficient vector of the intensity image. The convergence threshold of the algorithm is set to be $\varepsilon = 0.01$. After the algorithm converges, we obtain an optimal color component combination coefficient vector, and one discriminant projection vector φ^* (because there are two classes for gender recognition). Represent each color image A = [R,G,B] by its combined image D = $[R,G,B]X^*$. Then project all target and query images onto the discriminant projection vector and get their 1-D features. Based on the features of the target images, we calculate the class means of the male and the female, respectively.

These experimental results are completely consistent the conclusion, that is, the R component plays a more important role than the other two components, which has been revealed by CID algorithm. As a matter of fact, it is not hard to understand this from the natural color property of human faces, i.e., R is the principal component in the color of human faces.

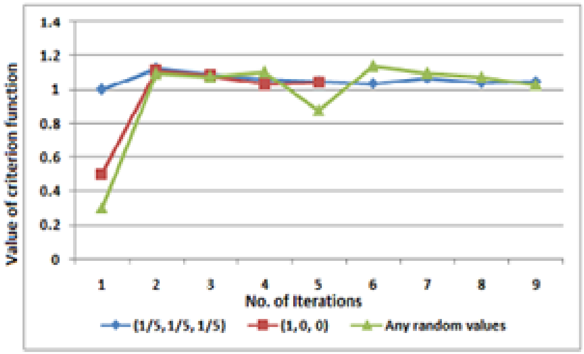

Figure 3: Illustration of the Convergence of the CID Algorithm

It should be pointed out that the convergence of the basic CID algorithm does not depend on the choice of the initial value of $X^{[0]}$. They experimented with other initial values, such as $X^{[0]} = [1,0,0]^T$ (corresponding to the R component image of an RGB color image) and a randomly generated 3-D vector. The convergence of the basic CID algorithm corresponding to these initial values is illustrated in Figure 3. The convergence of the CID algorithm is independent of the choice of initial value of $X^{[0]}$. The algorithm consistently converges to a very similar value of the criterion function $J(\varphi, X)$, and its convergence speed is fast: it always converges within ten iterations if $\varepsilon = 0.01$ is choosen.

CONCLUSIONS

Results reported in these works indicate that face color information can play an important role in gender recognition. To find a meaningful representation and an effective recognition method of color images in a unified framework; CID model is an integrate color image representation and gender recognition into one discriminant model.

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